Designing an Early Warning System Web Mapping Application for the Atlanta Metropolitan Area before a Flooding Event

by

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To my supportive family and friends, and my beautiful fiancé, for allowing me to work on this thesis and plan our wedding. I am finished now, so let's go and celebrate!

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Abbreviations

AMWA	Atlanta Metropolitan Web Application
AMA	Atlanta Metropolitan Area
API	Application Programming Interface
ARC	Atlanta Regional Commission
AGOL	ArcGIS Online
CSS	Cascading Style Sheet
DEM	Digital Elevation Model
FEMA	Flood Emergency Management Agency
GIS	Geographic Information System
HIFLD	Homeland Infrastructure Foundation-Level Data
HTML	Hypertext Markup Language
KMO	Kaiser-Meyer-Olkin
MEMA	Mississippi Emergency Management Agency
NFIP	National Flood Insurance Program
NOAA	National Oceanic and Atmospheric Administration
PC	Personal Computer
PCA	Principal Component Analysis
PX	Pixels
SMS	Short Messaging Service
SSI	Spatial Sciences Institute
SoVI	Social Vulnerability Index

SVI	Social Vulnerability Indices
SWAT	Soil and Water Assessment Tool
USC	University of Southern California

Abstract

Hurricanes and heavy rainfall continue to cause flooding events. There is a need for researchers and other organizations to develop web and mobile applications to assist with flooding by studying vulnerabilities, traffic congestion, and decision making to evacuate or shelter in place. The Atlanta Metropolitan Area has not experienced a flooding event in nearly 10 years. Still, if a flood occurred, it could be as catastrophic as Hurricane Harvey was in Houston or Hurricane Katrina was in New Orleans.

The Atlanta Metropolitan Area experienced a flooding event in 2009 that caused the displacement of almost 17,000 residents and resulted in the death of 10 people. This event motivated the development of a web application that could help users prepare before a flooding event. The application enables preparedness by allowing users to view the built and social environments in areas affected by previous floods on their mobile device or PC. By allowing the mobile device or PC to access their location, the user can view nearby shelters should evacuation become necessary. This application has the potential to bridge the communication gap between federal, state, and local officials, emergency responders, and the public before a flooding event.

This application has the potential to reduce loss of life and help with planning responses to future flooding events by identifying nearby shelters, and eventually helping individuals to develop ways to protect their homes and businesses from flooding.

Chapter 1 Introduction

Natural disasters cause economic loss and damages measured in billions of dollars; thousands of lives lost, and hundreds of thousands of homes destroyed (NOAA 2020). With the continued change in climate, natural disasters will become more severe. Flooding is one of the most destructive disasters causing damage each year, especially in urbanized areas such as the Atlanta Metropolitan Area (AMA), which experienced a seven-day flood event in September 2009. The AMA has not undergone significant flooding in 11 years, and with continued urbanization, another prolonged, extensive rainfall event could be catastrophic. This thesis project designed a geospatial web application to help Atlanta residents prepare for flooding events. Previously, there was no active flood preparedness web or mobile application for the AMA. This application gives Atlanta residents the necessary tools to understand flood risks and prepare for a flooding event.

1.1. Study Area

The AMA experienced a seven-day flooding event in 2009, causing damage worth $500 million. The flood of 2009 was caused by prolonged rainfall. This resulted in already saturated soil conditions becoming worse, making the region more susceptible to flooding. More than 20,000 homes, businesses, and other buildings sustained damage, with 16,981 residents displaced from their homes and 10 residents who passed away.

The AMA has a population of 5,710,795 people. It includes nine watersheds. These watersheds have been altered by urban development, population growth and global warming, which have led to increases in the frequency and intensity of floods (Karamouz et al. 2019). The AMA is one of the most rapidly urbanizing population centers in the United States (Wright et al.

2012). In 1950, the AMA had less than one million people, and by 2010 the population was over five million (Mackun and Wilson 2011; Cox 2015).

With this rapid population growth, more individuals are exposed to flood events and need to be prepared before an event occurs. A previous study used the HAZUS-MH model from the Federal Emergency Management Agency (FEMA), digital elevation models (DEMs) and the National Flood Insurance Program (NFIP) to approximate the number of housing units located in the floodplain (Ferguson and Ashley 2017).

Four counties – Cobb, Dekalb, Fulton, and Gwinnett – were selected as the study area (Figure 1).

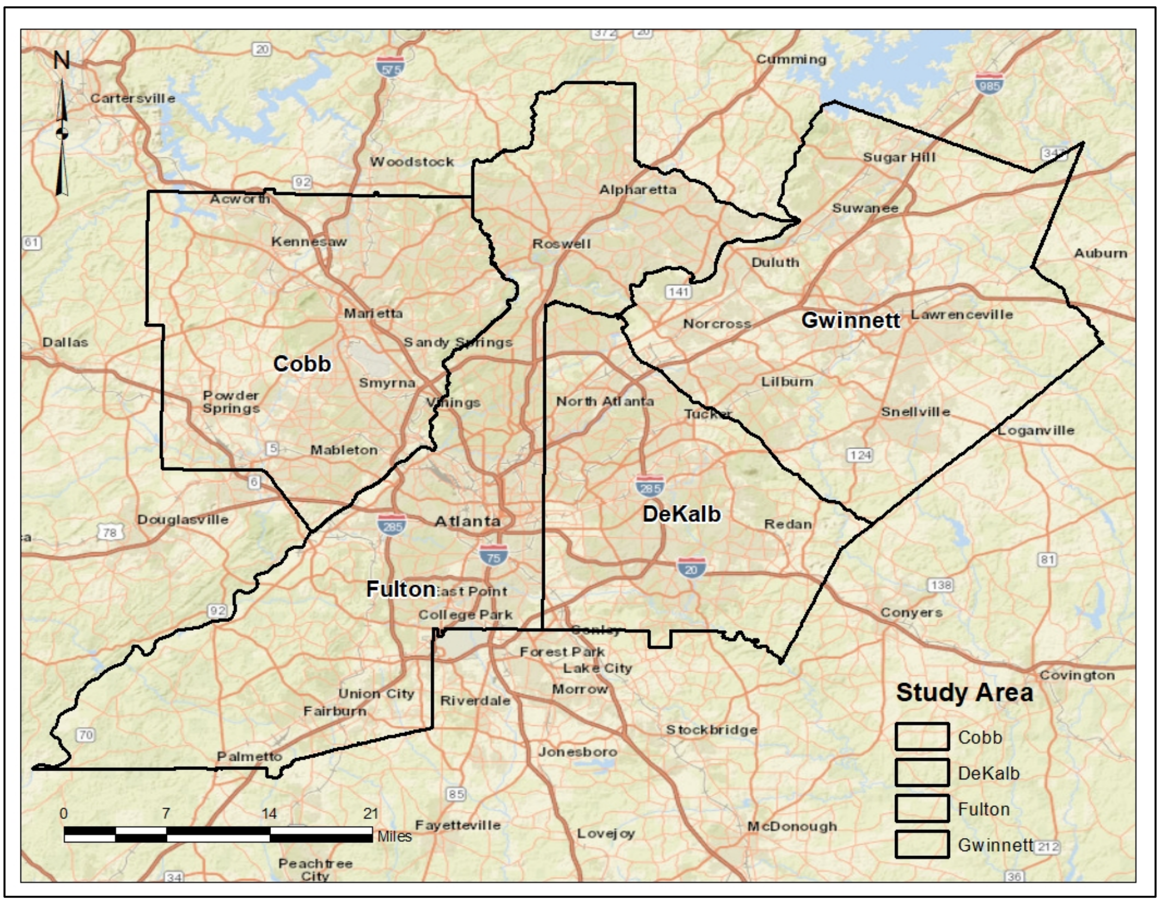

Figure 1. Map Showing Four Counties that Comprised the Study Area

These counties were some of the most affected counties in the 2009 flood and had the highest populations among the 29 counties in the AMA. Stream gages in these four counties had flood magnitudes much higher than the estimated 0.2-percent (500-year) and 0.5-percent (200-year) annual exceedance probabilities in 2009.

1.2. Motivation

This section explains the motivation for this research project. The concerns were to prevent loss of life and design an early warning system for Atlanta's residents. The following subsections explain these motivations in more detail to create an early warning flood system in a web mapping application to prevent loss of life and damage.

1.2.1. Loss of Life

Flooding from severe storms or extensive rainfall has caused the most fatalities in the United States from 2016 to 2020 with 3,505 deaths. Loss of life, economic loss, and the number of people affected are big concerns during floods. Flooding disasters have impacted over 2.3 billion people in the past 20 years by displacing them from their homes, the loss of loved ones, their businesses being destroyed, emotional stress, and other long-term effects. Kunreuther (1978) and Peek and Mileti (2002) found that people living in areas prone to natural hazards often fail to act, or do very little, to lessen their risk of death, injury, or economic loss.

Loss of life is exceptionally high for individuals in lower-income areas, minorities, the elderly, and the young. Hurricane Katrina, for example, resulted in more African American deaths than any other race (Sharkey 2007). Mortality rates for Hurricane Katrina were up to four times higher for blacks than whites (Brunkard et al. 2008), due to economic disadvantage, the residents' choice to evacuate if able, and not having the proper information to make informed decisions.

Park et al. (2020) state that people should move to the closest shelter as quickly as possible when the government issues an evacuation order; however, there are many barriers to this occurring. They noted how government issued evacuation orders do not tell evacuees where the nearest shelter is and the easiest path to access them. So, lacking information, people cannot determine which shelter is closest and the easiest for them to access and leads to individuals being trapped in their homes, on streets, or in a traffic jam. Maghelal et al. (2017) explained that 90 of the 93 people who lost their lives during Hurricane Rita in Houston, Texas, died because of traffic congestion. Some individuals decide to shelter in place, or they receive evacuation orders too late. Haynes et al. (2018) explained that some individuals felt the official warnings were sufficient, but others had difficulty interpreting them.

1.2.2. Early Warning System

Early warning systems help reduce vulnerabilities to floods in urban and rural areas. Multiple studies have shown ways to integrate Geographic Information Systems and mobile/web applications to create an early warning system. Jakimovski et al. (2019) developed an Android app called Bewared that provides an early warning system using Facebook, Google Maps, and crowdsourcing. Hoffman and Schüttrumpf (2019) created a concept for a risk-based early warning system by linking rainfall-forecasting information together with a coupled hydro-numeric model and a GIS-system to predict pluvial flooding processes and their actual impacts.

Tarchiani et al. (2020) stated that an early warning system is the pillar of disaster risk reduction by integrating hazard monitoring, forecasting and prediction, disaster risk assessment, communication, and preparedness activities systems. This process enables individuals, communities, governments, businesses, and others to take timely action to reduce disaster risks in advance of hazardous events.

1.3. Application Overview

The Atlanta Metropolitan Emergency Preparation App allows Atlanta residents prepare for a flood event and explore relevant information. The Esri ArcGIS Application Programming Interface (API) for JavaScript using the Web AppBuilder was used to build the application. The intended users for this application are Atlanta residents, who can access the app on any device with a web browser. The application allows users to interact with the map using different widgets. The app enables users to zoom, pan, and find their device location on the map. The application displays different map layers as a user zooms in and out and enables users to click on the various layers and view the selected features information. The application allows users to turn map layers on and off. Users can also see the nearest shelter that is not in the floodplain and use the direction widget to know the distance to the shelter from their location.

1.4. Thesis Structure

The remainder of the thesis is comprised of four chapters. Chapter 2 describes the related work. Chapter 3 describes the methods and data used to construct the application. Chapter 4 describes the web application and how it can be used to manage flood risk. Chapter 5 offers some conclusions and recommendations for future work.

Chapter 2 Related Work

Due to the destructive nature of flooding events, researchers and emergency management officials continue to develop vulnerability maps, early warning systems, and ways to avoid or mitigate traffic during an evacuation before a flooding event. The web application developed for this thesis project will help with all these issues via taking advantage of people's daily mobile device usage. This chapter describes early warning systems and mobile applications and how they help users during natural disasters to prepare evacuation and traffic plans based on social and physical vulnerability maps. The chapter explains how floods have been examined in the past, and how authors are currently attempting to help individuals prepare for floods. This helped in the design of the Atlanta Metropolitan Web Application and webpage.

2.1. Early Warning Systems and Mobile Devices

Several projects have sought to create an emergency response system for medical purposes on mobile devices. Rajput et al. (2015) proposed a two-system method that allowed users in an emergency to report directly to the nearest emergency facility by using a client-server Geographic Information Systems (GIS), a mobile device, and Google web services. The application allows the user to select the emergency service needed (fire, police or medical), and use their mobile device location to direct the required staff to them. Nyamugama and Qingyun (2005) proposed creating an extensive wireless GIS network using a Java cellular phone as a GIS terminal for environmental monitoring through dynamic location disaster-emergency notification management of the spatial database. Their application managed spatial information such as flood hazards, fires, frost, and earthquakes and provided information to users at the earliest report of weather phenomena. Users could zoom into their location or an area of interest in the map and query weather status in the area or receive weather warnings. This article is dated given technological advancements since the project was conducted. Today, there are multiple applications that report the nearest lightning strike, heat advisory, and weather updates such as tornadoes, hurricanes, etc. However, this article provides steps to develop an early warning system using GIS and Java. Uddin and Awal (2013) proposed an early warning weather system as an added service and subscription for any mobile device. This system would alert subscribers through phone calls and short messaging services (SMSs) depending on their location relative to the natural disaster. The challenges with this method were: (1) the congestion of calls and messages; (2) non-subscribers would not receive a message; and (3) the application was dependent on individuals having a Java supported handset.

Hoffman and Schüttrumpf (2019) implemented an early warning system that took both the pluvial flood hazard and the vulnerability of urban infrastructure into account. These authors created a three-step model for an early warning system that consisted of: (1) a nowcasting system for provisioning short-term and radar-based rainfall forecasts; (2) a hydro-numerical model for the simulation of flow processes resulting from a heavy rainfall event; and (3) a GIS-model for the identification and classification of particularly vulnerable areas, and the estimation of damage values.

Early warning systems are necessary to motivate and help people needing to evacuate properly. Park et al. (2020) stated when a flood disaster happens, immediate evacuation is required, but it is difficult to use vehicles and other forms of public transportation. Therefore, it is necessary to identify the shortest path available for pedestrians as an escape route (Kim and Lee 2018). Evacuation is also dependent on the type of flood; for hurricanes and tropical storms, individuals can know that floods are possible in advance, unlike flash floods.

2.2. People, Transportation, and Evacuation

Transportation networks and evacuation have always been significant concerns when preparing for a natural disaster. For example, in 2014, two inches of snow shut down the AMA for 18 hours because it did not have an adequate snow plan. The result of this "snowstorm" was a standstill from January 28^{th} (Tuesday evening) to January 29th (Wednesday morning), and because traffic was congested, people abandoned their cars and hundreds of kids had to sleep over at their school (Davies 2014). Some of the reasons this occurred were poor communication, which resulted in traffic jams because Atlanta is the seventh worst among the country's metropolitan areas for traffic and with the storm occurring in the early afternoon, schools let kids out early, and people left work early to pick up their kids or avoid the snowstorm. Second, snow and ice on the roads and highways affected drivers because the roads were untreated. Atlanta residents did not understand the severity of the storm, and a lack of preparedness on the part of emergency officials caused major accidents and more traffic jams (Davies 2014).

Dow and Cutter (2002) explain how transportation issues have become more critical in coastal evacuations as traffic problems impinge on people's ability to get out of harm's way and ultimately influence their decision to evacuate. Based on news reports, weather, and traffic updates, some people evacuate when the first evacuation report occurs, others may wait a couple of hours or days depending on the storm's arrival, and others do not evacuate at all. Zheng and Cheng (2011) explained how the stalling and congestion of evacuation traffic could lead to risky traffic conditions and cause non-evacuation. Individuals and households tend to evacuate at different times than those specified in evacuation orders. This variability may increase loss of life and require emergency respondents to save more people. Maghelal et al. (2017) conducted a study that showed that not all people use their vehicles. Some took other means of transportation or walked to the nearest designated shelter, while others stayed and became trapped in their homes or business. Grothmann and Reusswig (2006) found that some residents take precautions for flooding, while others do not. These authors interviewed 157 people and asked them predetermined questions to determine how prepared they would be in flood. The interviews showed that 48% of the respondents prepared themselves for a flooding event, while the other 52% did not.

2.3. Social Vulnerability

Social vulnerability refers to communities' resilience when confronted by external stresses on human health, as happens with natural or human-caused disasters or disease outbreaks. Reducing social vulnerability can decrease both human suffering and economic loss. Social vulnerability focuses on the vulnerability of the human environment (Brooks 2003). Social vulnerability is not only related to individual characteristics such as gender, age, education, economic welfare, and race, but also the complex community dynamics and support systems that may influence specific individuals in their response to particular threats (Cutter et al. 2003; Mechanic and Tanner 2007).

Initially, social vulnerability indicators measured a place's social vulnerability based on socioeconomics and demographics. This method was later updated to include more demographic variables and became known as the Social Vulnerability Index (SoVI). Scholars have debated the validity of the SoVI in policy- and decision-making. Some scholars argue that SoVI represents communities, while others are skeptical.

Clark et al. (1998), Cutter et al. (2000), Tapsell et al. (2002), and Cutter et al. (2003) describe the foundations of social vulnerability mapping. Cutter et al. (2000) were among the first to create social vulnerability maps by identifying the most vulnerable populations groups who needed assistance during a hazard event.

Several years later, Cutter et al. (2003) developed the SoVI by reviewing hazard case studies at the county level. Based on U.S. Census data, 42 social variables were selected and normalized before a Principal Component Analysis (PCA) was performed. PCA was used to reduce the original correlated variables' dimensions by transforming them from the original correlated variables to a set of smaller uncorrelated variables (i.e., components). The SoVI score was calculated according to the component score, a positive or negative relationship with social vulnerability (Hadipour et al. 2020). These studies helped establish the methodologies that quantify and analyze spatial patterns of social vulnerability, and they continue to be used (Rufat et al. 2019).

Flanagan et al. (2011) developed a social vulnerability index (SVI) for disaster management by incorporating 15 census variables at the census tract level. The authors developed the SVI to improve all four phases of the disaster cycle: mitigation, preparedness, recovery, and response. The dataset included socioeconomic status, household composition and disability, minority status and language, and housing and transportation. After completing a case study in New Orleans, post-Katrina, the authors concluded that the SVI is flexible enough for use in different phases of disasters, notwithstanding certain limitations.

Shao et al. (2020) researched how to prepare a more concentrated social vulnerability map based on census tracts, unlike previous studies that used the county scale. These authors discuss how a populations' vulnerability should include the socio-demographic characteristics of those who may be affected and the level of exposure to physical hazards. This project sought to develop comprehensive indices that integrate social vulnerability into geophysical exposure (Cutter et al. 2010).

Rufat et al. (2019) analyzed four different social vulnerability models to assess their validity, including the SoVI, the weighted model based on expert knowledge, Social Vulnerability Indices (SVI), and the Social Vulnerability Profile (SVP). Initially, the social vulnerability profiles and the models correlated very well. After completing the model and pillar level validations, the authors completed an examination of the sub-dimensions of social vulnerability that are aligned with disaster outcomes. The author's term *pillar* represented SoVI components, SVI themes, weighted model pillars, and SVP profiles. After completing the validation and model, the authors explained that the SoVI and SVI were not as valid as the weighted index or SVP.

Said et al. (2019) integrated streamflow projections with social vulnerability by combining the SVI created by Flanagan et al. (2011) with the Soil and Water Assessment Tool (SWAT). Their approach supports the use of biophysical and socioeconomic factors to identify high-risk sub-basins and communities.

Spielman et al. (2020) show how the same data can result in different SoVI estimates. The authors also agreed with Rufat et al. (2019) that the best method was to specify variable weights without reliance on statistical techniques like PCA.

These studies show that there is no preferred method to create a social vulnerability map. The development of social vulnerability is dependent on the variables used, geographic extent, and scale.

2.4. Physical Vulnerability

Physical vulnerability maps are a useful tool for government officials, emergency respondents, and other organizations to determine which areas are most prone to flooding. Physical vulnerability models use different inputs, including transportation networks, flood hazards, flood depth, and community resiliency.

Zachos et al. (2016) developed over 800 vulnerability maps for the Mississippi Delta. The first 600 maps assessed the impact of flooding on transportation networks, and the other 200 consisted of a ten-day extent and flood depth from 0 to over 32 feet of water. These maps were constructed for the Mississippi Emergency Management Agency (MEMA) but were not available to the public. Remo et al. (2015) developed a flood vulnerability index to help planners screen the relative flood vulnerability across the entire state of Illinois. The results showed that half of the special flood hazard areas had low flood vulnerability, which enabled Illinois planners to focus on mitigation in critical locations.

Toma-Danila et al. (2020) studied how transportation networks and facilities can be affected by natural hazards, directly and indirectly, to aid in risk evaluation and mitigation planning. Luu et al. (2020) designed a flood risk assessment by multiplying hazard, exposure, and vulnerability to create a flood risk model. The goal was to assess the nature and extent of flood risk by analyzing potential flood hazards and evaluating existing flood exposure conditions and vulnerability that could potentially harm people, property, and livelihoods.

Kasmalkar et al. (2020) developed a flood resilience model based on road networks and their connectivity by integrating an existing traffic model with flood maps to find inundated roads. They established that measuring road network connectivity is a better proxy for quantifying a community's resilience to flood-related commute delays than flood exposure.

Most of these studies used flood depth, transportation networks, or flood hazards to develop physical vulnerability maps or community resiliency maps by also including demographics.

Chapter 3 Methodology

With the continued advancement of technology, information is readily available at any given time. Public access to flood information is necessary for decision making and education. This chapter explains the intended users, the application functionality, the map design, and the software requirements. The Atlanta Metropolitan Web Application (AMWA) will differ from the previous examples because the AMWA prepares the users before a flooding event. The AMWA gives necessary tools and the means to evacuate by helping users to find the nearest shelter within walking or driving distance, dependent on road accessibility and or shelter in place if their home is a viable solution. This thesis developed a social vulnerability map representing community resiliency based on a number of built and social environment characteristics.

3.1. Intended Users

The intended users of the AMWA are the residents of Cobb, Dekalb, Fulton, and Gwinnett counties. Users can access this web map before a flood event to better prepare themselves and their families. The web app aims to help users make decisions before a flooding event by providing flooding hazards, nearby shelters, and vulnerability maps to display which areas are more prone to flooding events. The web map accomplished this by showing a color scale with green specifying the safest areas and red indicating unsafe areas.

3.1.1. User Requirements

This application is accessible on any device with an internet connection or Wi-Fi. As mentioned above, the app is for the counties' residents, and the web map uses a straightforward design. The application will be accessible to anyone; no login information or payment is required. This application is accessible to people of all computer literacies with considerations made for older and younger users. Everitt (2019) designed an application for older adult users to prepare for an earthquake event in Los Angeles. This web application incorporated larger font sizes, readable text, high contrasting colors, and larger buttons. The AMWA design includes readable text, larger font sizes, and contrasting colors, but the developer decided on a specific color scheme for all age groups to help them visualize social and physical vulnerability.

3.2. Application Functionality

Some existing flood mapping applications were reviewed and used to guide this new web mapping application. The web app gives users the ability to pan and zoom in and out of the map application. The pan function allows users to move around the map to look at features. The zoom feature relates to the pan feature and enables users to zoom in or out when necessary to see certain features.

By adding the enable location tool, users can find themselves on the web map. When selecting the feature, the map will center and zoom to their location. This feature is necessary because users will see different map features when zooming to their location and can interact with them. Adding the enable location tool in the web application helps users reference their location in proximity to other elements and provides users with the necessary information about the area to prepare for a flooding event.

The fourth tool provided in the web mapping application is the legend and layer list. This tool allows users to find every map feature, receive more information about the area, and turn map layers on or off. The legend displays the map layers and how the layers are displayed, and when selected, the pop-up shows the selected information of the symbol. The layer list allows users to determine which map features are displayed. Users have the option to uncheck a map feature if desired.

The direction and near me tools were also added. The direction feature helps users determine the distance to the nearest shelter in the flood path. When users enable their location and see the various layers, the direction tool allows users to select layers in the map viewer. A user can switch means of travel between the two specified features by changing the directions from driving to walking and vice versa. A user can input their address or select the enable location feature in the near me tool, and it displays their location and the location of the nearest point features. Locating the nearest shelter, based on flooding extent and the user's location, is an essential part of the functionality. Users can already have a plan before a flooding event and decide what shelter to evacuate to if leaving their city or neighborhood is not possible.

The final tool added to the web mapping application was the print function. The print function gives users the ability to print the map view from their device to have a copy if they do not have good Wi-Fi connectivity.

3.3. Map Design

The first step in developing the map design was selecting the symbols for the features, including shelters, police stations, and hospitals. Each layer had a symbol chosen for identification in the web application. The symbols selected were based on basic symbols that everyone could easily identify. The police stations were shown as a badge with a capital P, the shelters with a house and a family holding hands, and hospitals with a capital H. The color chosen for these layers was blue because that resonates with stability and safety. The evacuation centers consist of community centers, schools, churches, and are based on the HIFLD national shelter system. These facilities represent a place that can house individuals in the event of an issued evacuation order and provide accurate locations of potential shelters in the event of a disaster. After selecting the symbols, each symbol covered up most of the map. So, to fix this issue, the size of the character had to be changed. The visibility of the symbols was modified so that the user was not overwhelmed with different symbols. The symbol's default size of 5.33 PX was increased to 20 PX because the shelters are the most critical element of the map.

3.4. Web Application Development

The importance of providing information to the public during a flood is essential for safety. With the lack of a mobile or web application for the AMA, flood information is not easily accessible or provided to residents. Creating a web application accessible on mobile devices and personal computers was essential to help residents safely prepare. The web application was created by utilizing data from various sources, including FEMA, the Census Bureau, and local entities in the Atlanta area. The remainder of this chapter explains the steps taken to develop the web application.

3.5. Function of Application

Since the AMA flood in 2009, this area has experienced isolated flooding events but nothing matching its extent. However, residents are still affected by these floods, and even with continued flooding, an application has not been developed to help residents. This demonstrates the need for a web application to help users delineate the areas most affected by flooding and the locations of nearby shelters to evacuate to. This application allows for non-GIS users to view the content of the application and interact with the data. It helps the user understand which areas are most affected by flooding, the locations of nearby shelters, and the directions to one or more shelters should one need to evacuate.

3.6. Data

The web map illustrates several different layers including the areas of minimum and maximum vulnerability for users to see if they are in a high or low risk group. The flood path is also provided in the web map to help users see areas more susceptible to flooding. Data was acquired from the Homeland Infrastructure Foundation-Level Data (HIFLD), FEMA, the Atlanta Regional Commission (ARC), and the U.S. Census Bureau, as summarized in Table 1. Once downloaded, some of the data and symbology were edited in Excel and ArcMap.

Table 1. Data for Web Application

Source	Contents	Data Type	Implementation
HIFLD	A nationwide geodatabase of shelters	Point	The shelters were clipped to the study area, and the symbology was changed in ArcGIS Online.
HIFLD	A nationwide geodatabase of police stations	Point	The police stations were clipped to the study area, and the symbology was changed in ArcGIS Online.
HIFLD	A nationwide geodatabase of hospitals	Point	The hospitals were clipped to the study area, and the symbology was changed in ArcGIS Online.
FEMA	A nationwide geodatabase of flooding	Vector	The layers were clipped to the study area, and specific flood designations were selected for the web application
ARC	State of Georgia County Borders	Vector	The study area county perimeters were clipped for the web application.
Census	Demographics, Housing, Ethnicity, Age	Point	The layer was edited in excel using PCA analysis and then uploaded into ArcMap. This layer was used to develop a social vulnerability map and uploaded it into ArcGIS Online.

3.7. Preparing the Data

The data acquired from the HIFLD is nationwide. For the data to be used in the web mapping application, the data was clipped to the borders of Cobb, Dekalb, Fulton and Gwinnett counties. After creating the flood vulnerability map, some shelters were within the flood path, and the nearest shelter for the user could be located outside of their designated county. So, to help users the flood path and shelters were extended beyond the four counties, giving users the ability to locate nearby shelters that avoided the flood paths. In ArcMap, the four counties in the designated study area were extracted from the State of Georgia shapefile and then the shelters, hospitals, and police stations were clipped to the study areas and a buffer surrounding them.

Once the data was clipped to the study area, the layers needed to be made accessible in the web mapping application. By clipping the layers to the study area, the data must be uploaded into ArcGIS Online (AGOL), but the files could not be directly imported. In ArcMap, each layer was selected individually and imported into ArcGIS Online as a layer package. When creating the layer package, the summary, tags, and description were filled and then it is possible to upload the layers into ArcGIS Online. Once in ArcGIS Online, the symbology for each layer was changed based on its designation as a shelter, hospital, or police station. The pixel size of the layers was changed so users would be able to view the layers in the web application more clearly and see the different symbols of the layers (Figures 2-3).

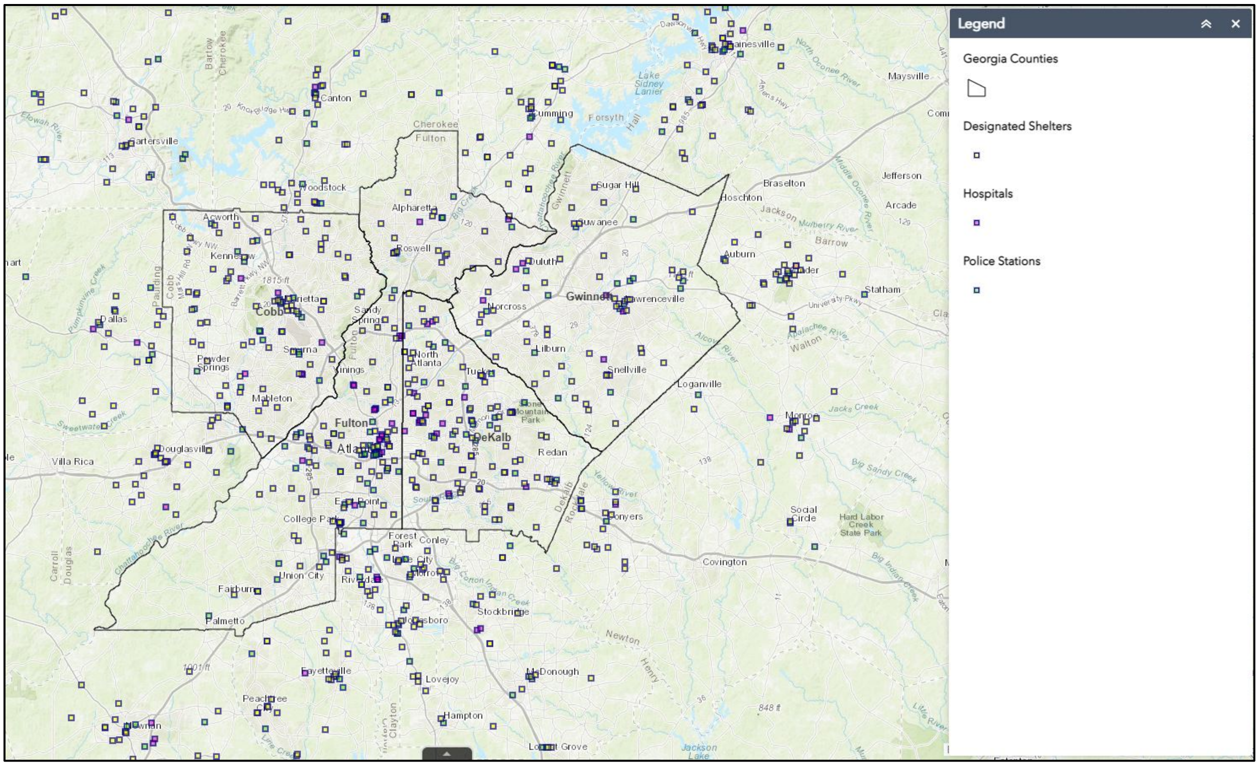

Figure 2. Shelters, Police Stations, and Hospitals and Study Area at 5.33 PX

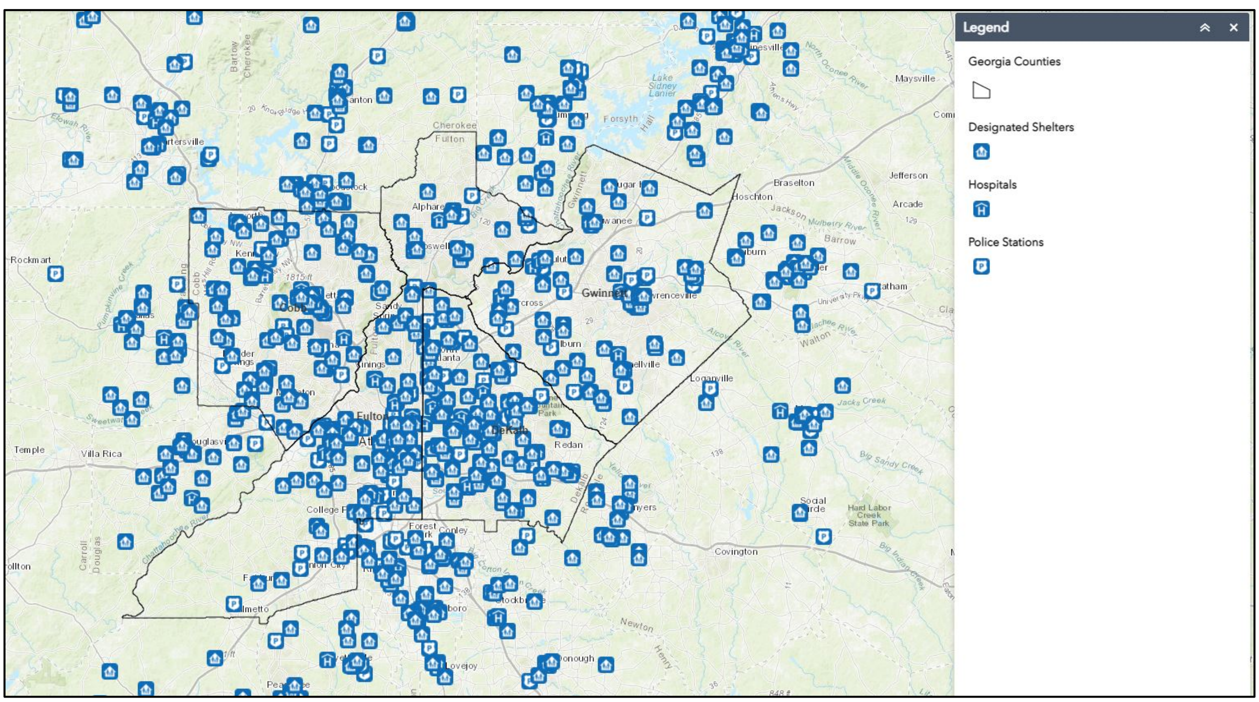

Figure 3. Shelter, Police Stations, and Hospitals at a size of 20 PX

As seen in Figure 3 the different layers clutter the web application, making it difficult to see all the layers clearly. This issue was fixed by using the visible range feature in AGOL by changing the visible range of each layer from state to cities. By changing the visibility when a user opens the web application the layers are not displayed first. The user must zoom into the map to bring out the shelters because they are hidden (Figure 4). This method was also completed for other layers including flood extent, social vulnerability, and physical vulnerability.

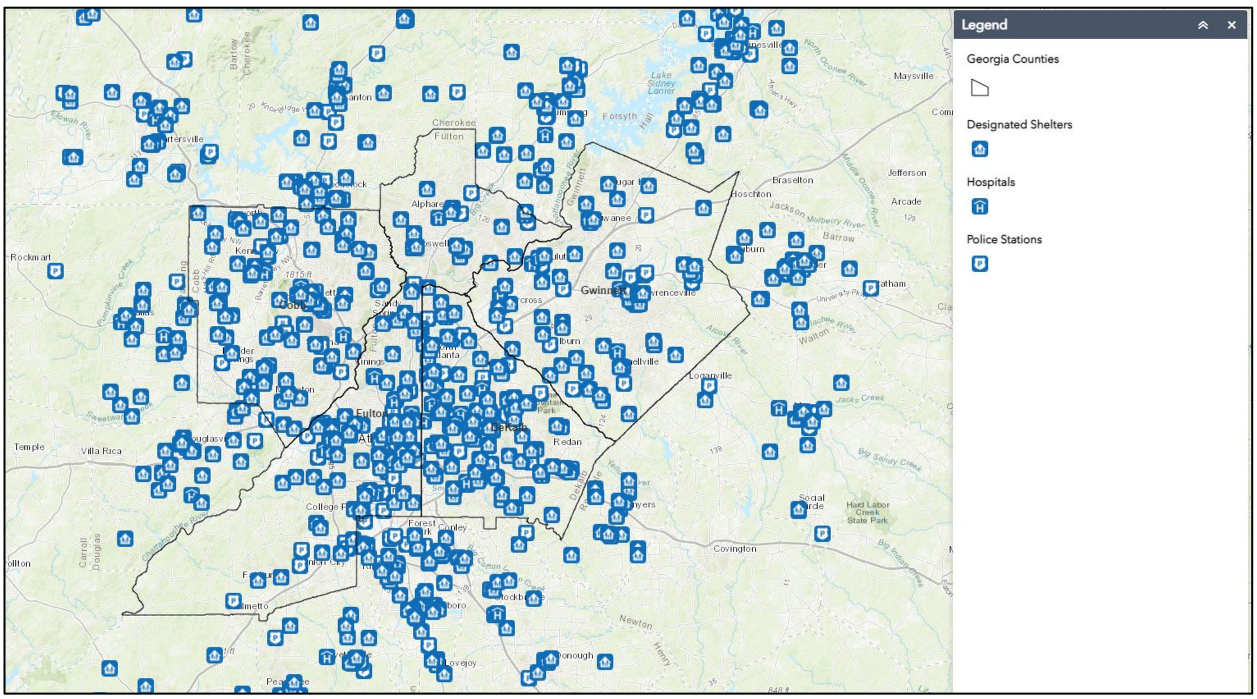

Figure 4. Map of Shelters, Police Stations and Hospitals after using Zoom

3.7.1. Flood Data

Creating the physical vulnerability in the web application required downloading the flood data from FEMA. In the FEMA flood mapping service center, the four counties had to be selected and downloaded separately. Each county was downloaded as a shapefile and imported into ArcMap and then using the attribute table, the flood data was changed to show three zones of flooding. Zone A describes areas subject to a one percent or greater annual chance of flooding in any given year. However, no base flood elevations are shown because detailed hydraulic analyses have not been performed on these areas. Zone AE describes areas subject to a one percent or greater annual chance of flooding in any given year and base flood elevations are shown as derived from detailed hydraulic analyses. Zone AO describes areas subject to a one percent or greater annual chance of shallow flooding in any given year. Flooding is usually in the form of sheet flow with average depths between one and three feet. Average flood depths are shown as derived from detailed hydraulic analyses (FEMA 2021). After changing how the zones were displayed, the merge feature was used to combine the four shapefiles into one shapefile. Once the shapefiles were merged, they were uploaded into ArcGIS Online by creating a layer package. By uploading the flood data to ArcGIS Online, the map viewer was utilized by changing the flood map's zoom feature, so the feature appears when users zoom in. Once the final changes were made, the flood data was uploaded into the web map application.

3.7.2. Principal Component Analysis

Principal component analysis (PCA) allows for the original set of variables to be condensed into smaller numbers by identifying trends and revealing the underlying factors that best represent the data variations through identification and clustering of variables that measure the same theme (Kazmierczak and Cavan 2011). The technique also facilitates replication of the variables at the district, provincial, and national levels and monitors the variables over time to assess any changes in overall vulnerability (Cutter et al. 2003). For this thesis, PCA was utilized to analyze a dataset of 20 variables based on: (1) socioeconomic status; (2) household composition and disability; (3) minority status and language; and (4) housing and transportation (Flanagan et al. 2011). The data was collected from the 2018 American Community Survey as an

Excel file for Dekalb, Cobb, Fulton, and Gwinnett Counties at the census tract level. The selected variables are listed in the Table 2.

Table 2. Variables Selected for PCA

Variable	**Abbreviation in Web Map**
Percent of Households with children < 18 years	CH_18UNDHH
Percent of households with a single parent	SNGPNT
Percent of households in which people live alone	LV_ALONE
Percent of population >= 65 years	POP_OVER65
Percent of adults >18 years with less than a high school diploma	NO_DIPLOMA
Percent of adults >= 18 years with a disability	AD_18OVDIS
Percent of population < 18 years with a disability	AD_18UNDIS
Percent of population >= 5 years that speaks English less than well	POP5OV_NOENG
Percent of households without a broadband internet subscription	HH_NOINTER
Percent of households without a computer	HH_NOPC
Percent of adults 18-65 years unemployed	UNEMPLOYED
Percent of housing units that are mobile homes	HHMOB_HOME
Percent of households without at least one vehicle	HHNO_VEHIC
Percent of households without telephone service	HHNO_TELE
Percent of renter occupied housing units	RENTER
Percent of population African American, Asian or Hispanic	MINORITY
Per Capita Income	PERCAPITA
Median Household Income	MND_HHIN
Percent of households with incomes less than the federal poverty threshold	POVERTY

This thesis used the approaches developed by Cutter et al. (2003) and Mavhura et al. (2017) to create the SoVI to estimate social vulnerability. The data was normalized before conducting the PCA. XLSTAT, an add-in tool for Excel, was used to upload the data and conduct all of the statistical analysis including varimax rotation, the Kaiser-Meyer-Olkin (KMO) metric, and Bartlett's Test of Sphericity. Varimax rotation produces more independence among the factors by simplifying the structure of the underlying dimensions (Mavhura et al. 2017). Varimax rotation also helps to minimize the number of variables that loaded high on a single factor, by increasing the percentage variation between each factor (Armas and Gavis 2013). The KMO criterion was applied for the component selection because only factors with eigenvalues greater than 1 are used. The KMO test measures how suited the data is for factor analysis. The test measures sampling adequacy for each variable in the model and the complete model. The statistic is a measure of the proportion of variance among variables that might be common variance. The KMO varies from 0 to 1 and values that are closer to 1 are adequate. A value of 0.6 is a suggested minimum and was used as the cutoff for this thesis project (Fekete 2012).

The Bartlett's Test of Sphericity tests the hypothesis that the correlation matrix is an identity matrix, which would indicate that the variables are unrelated and therefore unsuitable for structure detection. An identity matrix is one in which all the diagonal elements are 1 and all off-diagonal elements are 0 (Fekete 2012). The hypothesis needed to be rejected in this work, and this required p values < 0.05.

A PCA was completed for each county separately to develop an accurate SoVI. Tables 3-6 provide a list of the 20 variables used to develop the social vulnerability index at the census tract level. There are no missing values in the data for each county.

Varimax rotation was used to simplify the underlying dimensions' structure and produced more independence among the factors (Mavhura et al. 2017). The Kaiser criterion (eigenvalues > 1) was applied for the component selection. To check the model's robustness, two statistical tests, the KMO of sampling adequacy and Bartlett's Test of Sphericity, were used (Mavhura et al. 2017). The KMO test was meant to measure the sampling adequacy and evaluate the correlations and partial correlations to determine if the data were likely to coalesce on components (Mavhura et al. 2017). The KMO measure varies between 0 and 1, and values that are closer to 1 are adequate.

Table 3. Descriptive statistics of selected variables for Cobb County

Variable	Observations	Obs. with missing data	Obs. without	Minimum	Maximum	Mean	Std. deviation
Percent of Households with children < 18 years	120	0	120	8.500	48.700	32.683	8.935
Percent of households with a single parent	120	0	120	1.800	29.300	9.252	5.552
Percent of households in which people live alone	120	0	120	3.700	52.000	23.692	11.094
Percent of population >= 65 years	120	0	120	3.360	27.460	9.616	3.430
Percent of adults >18 years with less than a high school diploma	120	0	120	10.900	58.600	27.428	10.331
Percent of adults >= 18 years with a disability	120	0	120	10.200	71.100	36.176	12.554
Percent of population < 18 years with a disability	120	0	120	0.000	18.100	3.425	2.693
Percent of population >= 5 years that speaks English less than well	120	0	120	0.500	31.500	7.348	6.360
Percent of households without a computer	120	0	120	79.300	100.000	95.691	3.868
Percent of households without a broadband internet subscription	120	0	120	66.100	99.000	89.676	7.715
Percent of adults 18-65 years unemployed	120	0	120	0.500	7.800	3.501	1.521
Percent of housing units that are mobile homes	120	0	120	0.000	22.300	1.202	2.903
Percent of households without at least one vehicle	120	0	120	0.000	20.700	3.782	4.285
Percent of households without telephone service	120	0	120	0.000	5.000	1.553	1.076
Percent of renter occupied housing units	120	0	120	0.000	94.300	73.142	10.032
Percent of population African American, Asian or Hispanic	120	0	120	10.100	111.600	49.032	26.874
Per Capita Income	120	0	120	13390.000	112315.000	39323.383	15333.744
Median Household Income	120	0	120	27216.000	178819.000	83181.275	32637.017
Percent of households with incomes less than the federal poverty threshold	120	0	120	0.000	37.800	7.463	7.171

Table 4. Descriptive statistics of selected variables for Dekalb County

Variable	Observations	Obs. with missing data	Obs. without	Minimum	Maximum	Mean	Std. deviation
Percent of Households with children < 18 years	144	0	144	0.000	56.600	26.294	9.766
Percent of households with a single parent	144	0	144	0.000	40.400	18.560	10.208
Percent of households in which people live alone	144	0	144	0.000	59.600	32.356	10.313
Percent of population >= 65 years	144	0	144	0.000	62.300	30.758	14.260
Percent of adults >18 years with less than a high school diploma	144	0	144	3.200	132.050	31.955	18.259
Percent of adults >= 18 years with a disability	144	0	144	0.093	27.203	9.398	5.983
Percent of population < 18 years with a disability	144	0	144	0.000	3.228	0.672	0.745
Percent of population >= 5 years that speaks English less than well	144	0	144	0.000	74.077	9.303	13.793
Percent of households without a computer	144	0	144	0.000	98.447	23.178	33.816
Percent of households without a broadband internet subscription	144	0	144	0.000	190.714	23.661	20.370
Percent of adults 18-65 years unemployed	144	0	144	0.000	99.689	75.431	14.153
Percent of housing units that are mobile homes	144	0	144	0.000	8.899	0.344	0.922
Percent of households without at least one vehicle	144	0	144	0.000	38.698	7.636	7.682
Percent of households without telephone service	144	0	144	0.000	5.300	1.601	1.163
Percent of renter occupied housing units	144	0	144	0.000	93.734	60.567	28.464
Percent of population African American, Asian or Hispanic	144	0	144	5.783	100.000	67.258	32.184
Per Capita Income	144	0	144	9356.000	100545.000	35834.160	19466.830
Median Household Income	144	0	144	0.000	184875.000	67068.854	34089.054
Percent of households with incomes less than the federal poverty threshold	144	0	144	0.000	59.400	13.123	10.423

KMO values greater than 0.6 were used for this thesis project. The KMO value was 0.875 for Fulton County, 0.860 for Cobb County, 0.689 for Dekalb County, and 0.831 for Gwinnett County. XLSTAT also indicated that the data for each county was appropriate for the component analysis (Mavhura et al. 2017).

Table 5. Descriptive statistics of selected variables for Fulton County

Variable	Observations	Obs. with missing data	Obs. without	Minimum	Maximum	Mean	Std. deviation
Percent of Households with children < 18 years	203	0	203	0.000	60.700	24.004	12.305
Percent of households with a single parent	203	0	203	0.000	56.400	10.284	8.214
Percent of households in which people live alone	203	0	203	0.000	88.600	39.133	15.661
Percent of population >= 65 years	203	0	203	0.000	188.600	31.739	20.315
Percent of adults >18 years with less than a high school diploma	203	0	203	5.000	62.800	26.728	12.542
Percent of adults >= 18 years with a disability	203	0	203	0.000	91.800	44.581	19.776
Percent of population < 18 years with a disability	203	0	203	0.000	20.400	3.919	4.133
Percent of population >= 5 years that speaks English less than well	203	0	203	0.000	45.500	4.485	6.048
Percent of households without a computer	203	0	203	0.000	43.900	10.567	10.016
Percent of households without a broadband internet subscription	203	0	203	0.000	55.700	20.068	14.737
Percent of adults 18-65 years unemployed	203	0	203	0.000	19.800	4.879	3.859
Percent of housing units that are mobile homes	203	0	203	0.000	15.000	0.626	1.543
Percent of households without at least one vehicle	203	0	203	0.000	52.600	14.109	12.755
Percent of households without telephone service	203	0	203	0.000	12.300	2.534	2.161
Percent of renter occupied housing units	203	0	203	0.000	100.000	69.607	15.543
Percent of population African American, Asian or Hispanic	203	0	203	0.722	104.513	49.768	36.864
Per Capita Income	203	0	203	4471.000	145969.000	42506.207	27412.423
Median Household Income	203	0	203	0.000	210667.000	70131.798	44561.486
Percent of households with incomes less than the federal poverty threshold	203	0	203	0.000	37.200	8.211	5.726

Table 6. Descriptive statistics of selected variables for Gwinnett County

Variable	Observations	Obs. with missing data	Obs. without	Minimum	Maximum	Mean	Std. deviation
Percent of Households with children < 18 years	113	0	113	17.200	57.700	37.627	7.518
Percent of households with a single parent	113	0	113	3.800	31.200	17.058	6.195
Percent of households in which people live alone	113	0	113	4.700	52.000	21.311	9.250
Percent of population >= 65 years	113	0	113	2.300	57.000	24.956	10.190
Percent of adults >18 years with less than a high school diploma	113	0	113	8.400	56.100	32.869	9.463
Percent of adults >= 18 years with a disability	113	0	113	0.600	58.000	33.432	11.129
Percent of population < 18 years with a disability	113	0	113	0.000	7.900	2.221	1.946
Percent of population >= 5 years that speaks English less than well	113	0	113	2.500	47.300	16.630	10.860
Percent of households without a computer	113	0	113	0.000	24.599	5.316	4.406
Percent of households without a broadband internet subscription	113	0	113	1.171	47.301	13.775	9.167
Percent of adults 18-65 years unemployed	113	0	113	0.700	8.600	3.342	1.425
Percent of housing units that are mobile homes	113	0	113	0.000	19.700	1.532	3.103
Percent of households without at least one vehicle	113	0	113	0.000	14.500	3.635	3.154
Percent of households without telephone service	113	0	113	0.000	7.100	1.653	1.359
Percent of renter occupied housing units	113	0	113	6.200	67.600	30.365	13.392
Percent of population African American, Asian or Hispanic	113	0	113	1.153	74.857	39.667	16.250
Per Capita Income	113	0	113	14812.000	67269.000	28882.487	9348.105
Median Household Income	113	0	113	33020.000	156136.000	69439.239	24358.436
Percent of households with incomes less than the federal poverty threshold	113	0	113	0.900	28.800	10.364	6.911

Tables 7-10 show the results from the Bartlett's Test for each county. The null hypothesis that there was no correlations that were significantly different from 0 between the variables was rejected and the alternative hypothesis that was at least one of the correlations between the variables that was significantly different from 0 was accepted. This was because the computed p-value was lower than the chosen significance level ($p = 0.05$).

Table 7. Bartlett's Test Results for Cobb County

Bartlett's sphericity test:	
Chi-square (Observed value)	1773.970
Chi-square (Critical value)	202.513
DF	171
p-value (Two-tailed)	< 0.0001
Alpha	0.05

Table 8. Bartlett's Test Results for Dekalb County

Bartlett's sphericity test:	
Chi-square (Observed value)	2026.981
Chi-square (Critical value)	202.513
DF	171
p-value (Two-tailed)	< 0.0001
Alpha	0.05

Table 9. Bartlett's Test Results for Fulton County

Bartlett's sphericity test:	
Chi-square (Observed value)	3539.265
Chi-square (Critical value)	202.513
DF	171
p-value (Two-tailed)	< 0.0001
Alpha	0.05

Table 10. Bartlett's Test Results for Gwinnett County

Bartlett's sphericity test:	
Chi-square (Observed value)	1663.012
Chi-square (Critical value)	202.513
DF	171
p-value (Two-tailed)	< 0.0001
Alpha	0.05

After verifying that the KMO and Bartlett's Test of Sphericity passed the minimum standard the remainder of the PCA analysis in XLSTAT could be reviewed. Of the 19 variables that were used for the PCA, 10 components were selected because they explained greater than 2 percent of the cumulative variance in each county. Cobb County had 11 components with scores greater than 2 percent. DeKalb and Gwinnett had 10 components with scores greater than 2 percent. Fulton County had nine components with scores greater than 2 percent. The top 10 components were used in the four counties to maximize consistency. The eigenvalues and cumulative variance in each county are summarized in Tables 11-14.

The eigenvalues shown in Tables 11-14 also depict the variances of the principal components. When running the PCA in XLSTAT the correlation matrix allows each of the 19 variables to have a variance of 1 and the total variance was equal to the number of variables used in the analysis (Mavhura et al. 2017). With the first component representing the most variance and the highest eigenvalue, the subsequent components describe the remainder of the variance not explained by the earlier components.

A SoVI score was developed by adding all 10 component scores for each census tract in the four counties. Table 15 shows how the SoVI were calculated for a sample of census tracts located in Cobb county. Components that increased vulnerability were considered positive, and those that reduced vulnerability were viewed as negative (Solangaarachchi et al. 2012). In this way, each factor was viewed as having an equal contribution to the overall vulnerability of each census tract. The focus is on spatial variability and understanding the complexities of the vulnerability explanations (Mavhura et al. 2017). Weights were not assigned and the final SoVI scores were classified using the standard deviation method.

Table 11. Total Variability and Eigenvalues of Cobb County

Component	Eigenvalue	Variability Explained (%)	Cumulative Variability (%)
F1	8.20	43.16	43.16
F2	2.16	11.38	54.54
F3	1.52	7.99	62.53
F4	1.18	6.18	68.71
F5	0.96	5.04	73.76
F6	0.86	4.53	78.29
F7	0.80	4.24	82.52
F8	0.63	3.33	85.85
F9	0.54	2.86	88.71
F10	0.47	2.47	91.18
F11	0.45	2.39	93.56
F12	0.30	1.59	95.15
F13	0.22	1.17	96.32
F14	0.20	1.06	97.38
F15	0.15	0.79	98.16
F16	0.12	0.62	98.78
F17	0.11	0.57	99.35
F18	0.08	0.44	99.79
F19	0.04	0.21	100.00

Table 12. Total Variability and Eigenvalues of Dekalb County

Component	Eigenvalue	Variability Explained (%)	Cumulative Variability (%)
F1	4.77	25.10	25.10
F2	3.84	20.23	45.33
F3	2.02	10.65	55.99
F4	1.90	9.99	65.98
F5	1.12	5.90	71.88
F6	0.93	4.90	76.78
F7	0.87	4.59	81.37
F8	0.76	4.02	85.39
F9	0.68	3.60	88.99
F10	0.46	2.41	91.40
F11	0.37	1.96	93.36
F12	0.35	1.83	95.19
F13	0.26	1.38	96.56
F14	0.20	1.07	97.63
F15	0.15	0.80	98.44
F16	0.11	0.60	99.04
F17	0.10	0.50	99.54
F18	0.05	0.27	99.80
F19	0.04	0.20	100.00

Table 13. Total Variability and Eigenvalues of Fulton County

Component	Eigenvalue	Variability Explained (%)	Cumulative Variability (%)
F1	8.63	45.40	45.40
F2	2.25	11.84	57.23
F3	1.69	8.90	66.13
F4	1.23	6.46	72.60
F5	1.02	5.39	77.99
F6	0.80	4.23	82.21
F7	0.73	3.83	86.04
F8	0.52	2.73	88.77
F9	0.40	2.09	90.86
F10	0.38	1.99	92.86
F11	0.32	1.71	94.56
F12	0.26	1.37	95.94
F13	0.22	1.14	97.08
F14	0.15	0.81	97.89
F15	0.13	0.67	98.56
F16	0.10	0.50	99.06
F17	0.08	0.40	99.46
F18	0.05	0.28	99.74
F19	0.05	0.26	100.00

Table 14. Total Variability and Eigenvalues of Gwinnett County

Component	Eigenvalue	Variability Explained (%)	Cumulative Variability (%)
F1	7.45	39.20	39.20
F2	2.07	10.90	50.10
F3	1.86	9.77	59.87
F4	1.50	7.89	67.75
F5	1.06	5.57	73.33
F6	0.89	4.67	78.00
F7	0.86	4.54	82.53
F8	0.81	4.28	86.81
F9	0.49	2.59	89.40
F10	0.44	2.30	91.69
F11	0.32	1.70	93.39
F12	0.30	1.58	94.97
F13	0.27	1.42	96.39
F14	0.23	1.19	97.58
F15	0.15	0.81	98.39
F16	0.13	0.68	99.07
F17	0.08	0.44	99.51
F18	0.05	0.26	99.76
F19	0.04	0.24	100.00

Table 15. SoVI Scores for Cobb County Based On Census Tracts

Census Tract Name	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	SoVI Score
Census Tract 301.01, Cobb County, Georgia	-0.353	-0.401	1.018	-0.833	0.117	-1.243	0.525	0.183	0.851	-0.238	-0.373
Census Tract 301.03, Cobb County, Georgia	-0.301	-0.885	0.109	-1.441	0.468	-0.853	0.660	0.255	1.056	0.322	-0.609
Census Tract 301.04, Cobb County, Georgia	2.395	0.786	2.048	0.021	0.229	0.440	0.155	-0.516	-0.031	-2.053	3.473
Census Tract 301.06, Cobb County, Georgia	1.555	-0.074	-0.146	-1.439	0.411	-0.156	-1.084	0.239	-0.498	-0.372	-1.564
Census Tract 301.07, Cobb County, Georgia	-1.253	-1.611	-1.035	-0.114	1.330	-0.249	-0.769	-0.455	0.378	-0.622	-4.398
Census Tract 302.09, Cobb County, Georgia	-1.426	-0.271	0.127	-0.503	-0.166	0.235	-0.106	1.533	-0.120	0.036	-0.660
Census Tract 302.14, Cobb County, Georgia	-1.180	0.928	-1.208	-0.429	-0.381	0.404	-0.249	1.021	0.332	0.365	-0.396
Census Tract 302.15, Cobb County, Georgia	-0.066	-2.311	0.456	-1.485	-0.142	-1.125	1.909	0.330	0.823	0.574	-1.037
Census Tract 302.18, Cobb County, Georgia	-3.440	-2.134	0.274	0.098	-0.596	-0.425	-0.952	0.301	-0.119	0.513	-6.481
Census Tract 302.19, Cobb County, Georgia	-2.372	-1.911	-0.251	-0.484	-0.517	0.177	-0.568	0.697	0.215	-0.488	-5.503
Census Tract 302.20, Cobb County, Georgia	-1.351	-0.852	0.768	-0.126	0.174	0.016	0.085	-0.019	0.932	-1.351	-1.725
Census Tract 302.22, Cobb County, Georgia	-2.122	-0.629	-0.334	-0.114	0.442	0.117	-0.324	0.772	-0.707	-0.034	-2.933
Census Tract 302.23, Cobb County, Georgia	0.206	0.846	-0.648	0.436	0.907	0.012	1.208	0.198	-0.925	-0.279	1.961
Census Tract 302.24, Cobb County, Georgia	-0.796	-0.903	-0.567	0.431	0.915	0.339	-0.213	-0.244	-1.512	-0.893	-3.444

After calculating the composite SoVI scores, the data was uploaded to ArcMap 10.8 by joining the geo-id of the excel file and census shapefile. The SoVI scores ranged from 11.74 (the most vulnerable) to -13.84 (the least vulnerable). The composite SoVI scores were divided into five SoVI classes using the standard deviation method in ArcMap to illustrate the census tracts with the most to least risk in terms of social vulnerability (Figure 4). The > 1.5, 0.5 to 1.5, -0.5 to 0.5, -1.5 to -0.5, and < -1.5 standard deviation cutoffs were used to construct the classes shown in the legend of Figure 5.

3.7.3. Physical Vulnerability

Flood damage models predict the amount of damage a flood could cause to communities and infrastructure. The flood's intensity affects communities and can cause long-term economic damage. This thesis project will help users to delineate areas that may be affected by a flood and show physical vulnerability based on their proximity to the flood path. Users can input their home address or business location. The information can be used to evacuate to nearby shelters and prepare their homes or business accordingly.

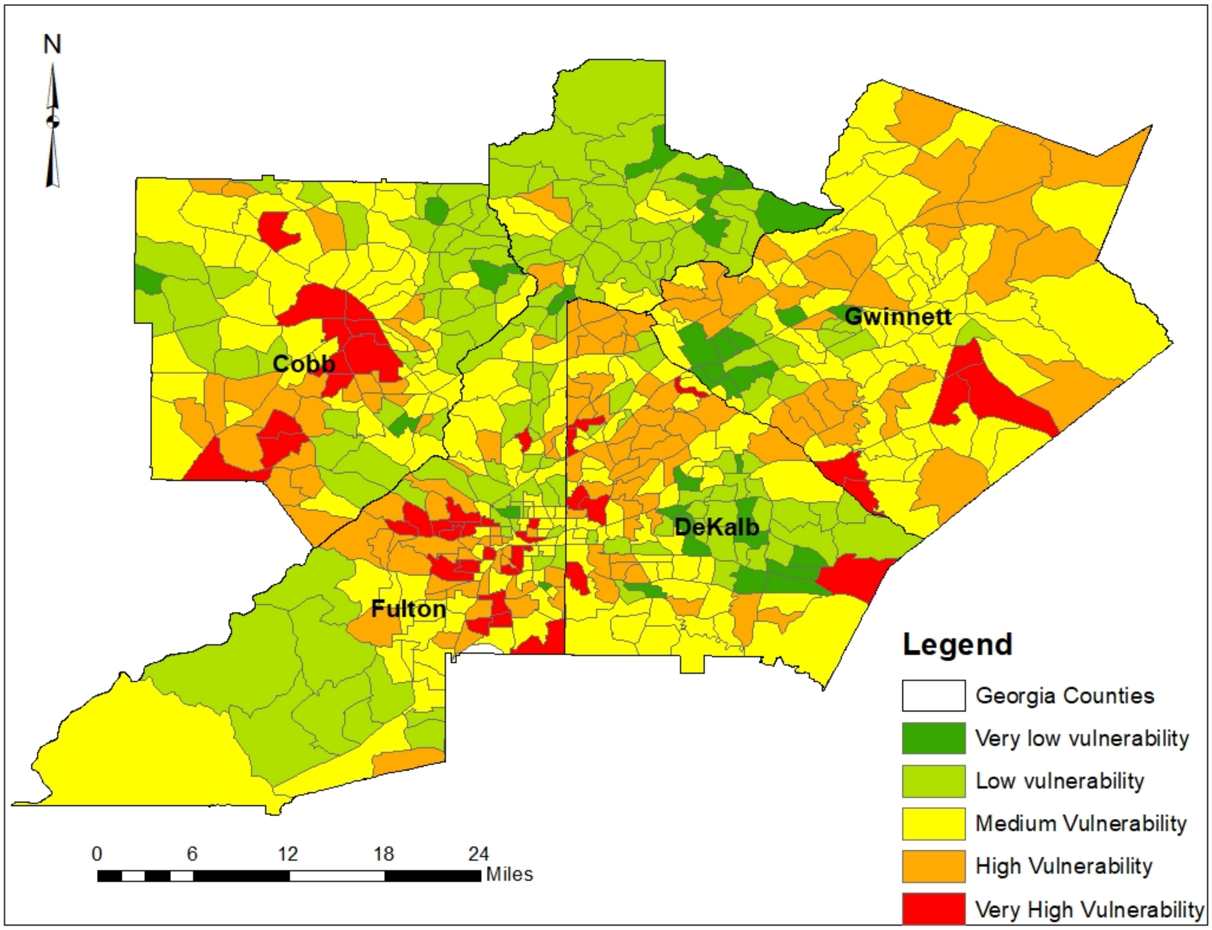

Figure 5. Variations in Social Vulnerability By Census Tract

After completing the PCA and uploading the social vulnerability map into ArcGIS Online as a hosted feature layer, the next part of the thesis was developing the physical vulnerability map. AGOL can be used to create a personal vulnerability map with a more streamlined, simpler workflow than in ArcGIS Pro and ArcMap. To create the physical vulnerability map in AGOL the census data was used with roads, shelters, and the flood path. This was accomplished by using the derive new location tool because it creates new features based on one or more attributes or spatial queries. In the map viewer for AGOL the perform analysis tool was selected for the census tract layer. Once selected, multiple tools appear in the map viewer and the find locations was selected. After selecting the find locations tool, the derive new location feature was chosen.

An expression box to build a query appears after selecting the derive new location feature. After entering the query in the expression, the run analysis can be selected.

The expression included the census tract data from the four counties, shelters, hospitals, police stations, flood paths, and roads.

The variable selected in the census data was people without at least one vehicle. This variable was selected to show how someone without a vehicle could be affected by a flood and need to evacuate. Before creating the query, an accurate threshold needed to be determined by examining the statistics of households without a vehicle. To see the statistics of households without a vehicle the census tract attribute table was selected and then in the attribute table the feature households without a vehicle was right-clicked to select statistics. A pop-up window appears with the amount, sum of values, minimum, maximum, average, and standard deviation (Figure 6).

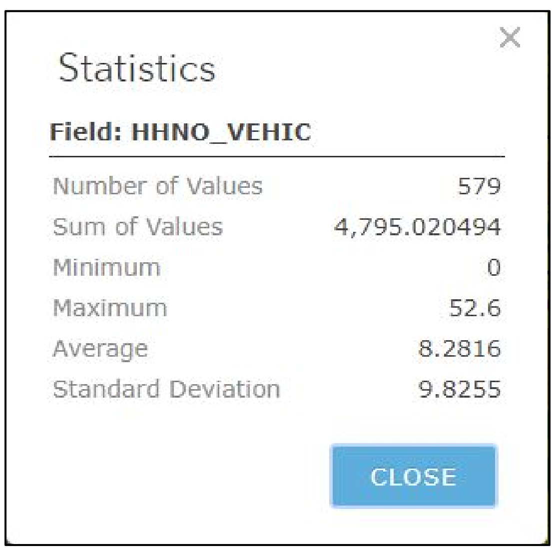

Figure 6. Statistics for People Without a Vehicle

The derive new location tool was used to determine households without a vehicle, their proximity to flood paths within the study area, and shelters to identify vulnerable areas. The shelters were included in the query as a reference point for people without a vehicle. The average

(8.28) and standard deviation (STD) (9.82) values were used in the query. These values represent the threshold for households without a vehicle. The first expression represents areas with the highest risk and is based on households without a vehicle, so the sum was calculated using the STD and the average, which equaled 18.1. This number determined the threshold for census tracts with a high number of households without a vehicle. The next step is to change the query to census tract where households without a vehicle is greater than 18.1 and then click add. After adding this expression, the add expression box was clicked again to add the expression census tract < 0.25 miles from the flood hazard. This returned all the census tracts in the study area within a quarter mile of a flood path. Once this expression was added, the run analysis tool was selected, and a map was created. The color for the default symbology was blue but then was changed to red to indicate danger (Figure 7).

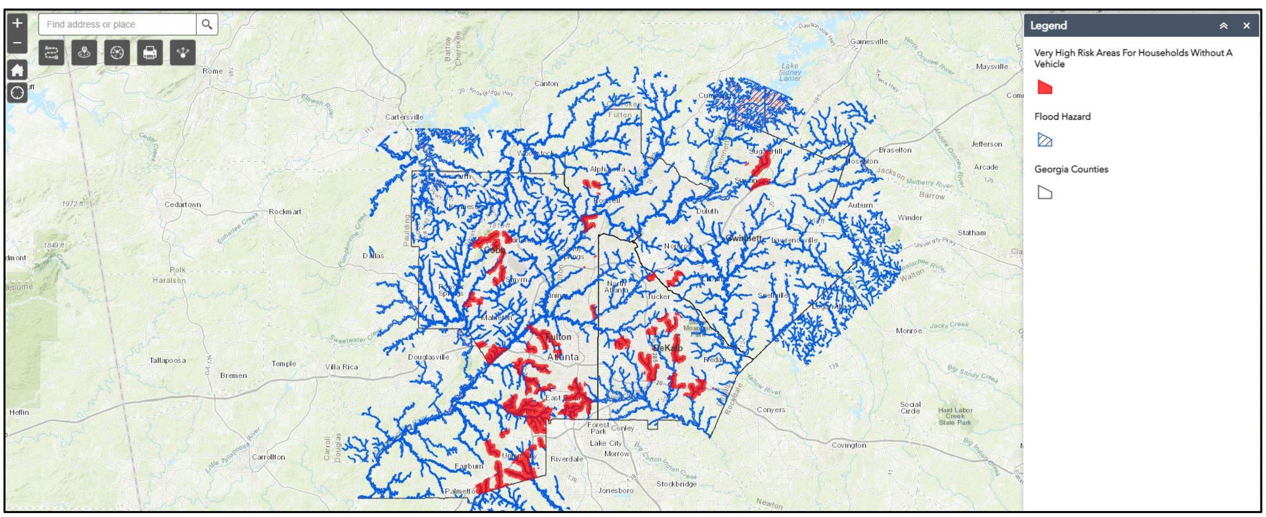

Figure 7. Very High Risk Flood Areas For Households With No Vehicle

This process of writing queries in the expression box was repeated four times in AGOL by selecting the new layer (i.e., High Risk – No Vehicle) and using the rerun analysis tool to modify the previous query. However, a lower number of households was adopted to decrease the risk attributed to households without a vehicle. This new expression was used to select census tracts with between 8.28 and 18.1 households without at least one vehicle. The new layer was mapped, and the color of the qualifying census tracts changed from the default to orange (Figure 8).

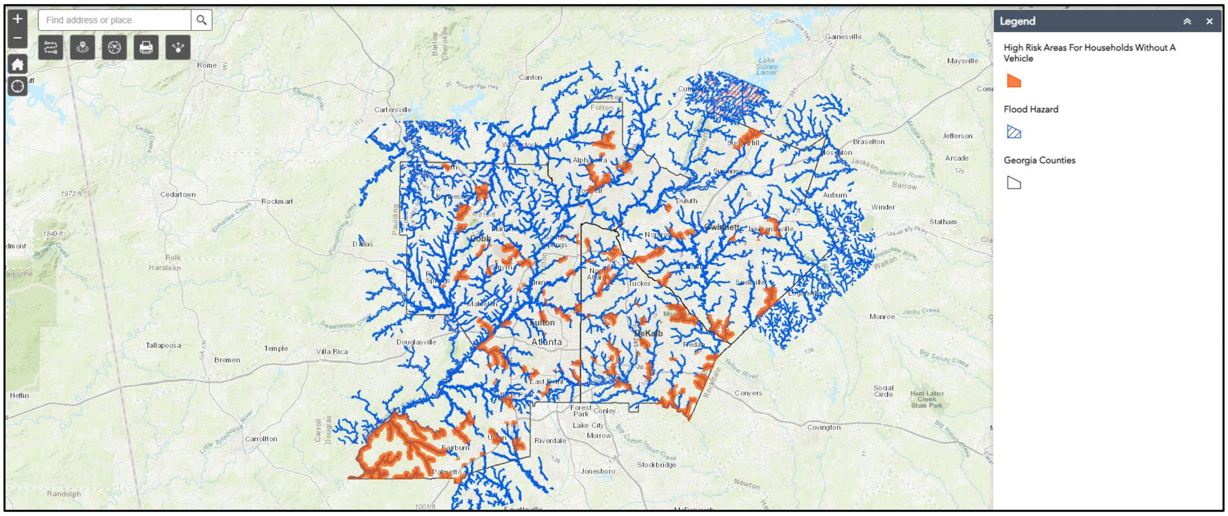

Figure 8. High Risk Flood Areas For Households With No Vehicle

Three more queries were made to capture the social vulnerability for households without a vehicle. The first selected households without a vehicle within 1 mile of a shelter. The second selected census tracts with less than 8.28 households without a vehicle and that were further than 1 mile from a shelter. The third query relaxed both the number of households without a car (similar to query 1) and the distances between census tracts and shelters (similar to query 2). The maps reproduced in Figures 9 and 10 show the five social vulnerability classes as a single hue. The red shows census tracks with very high-risk areas for households without a vehicle. The orange shows census tracks with high-risk areas for households without a vehicle. The yellow shows census tracks with medium risk areas for households without a vehicle. The light green shows census tracks with low-risk areas for households a vehicle. and the dark green shows census tracks with very-low risk areas for households without a vehicle.

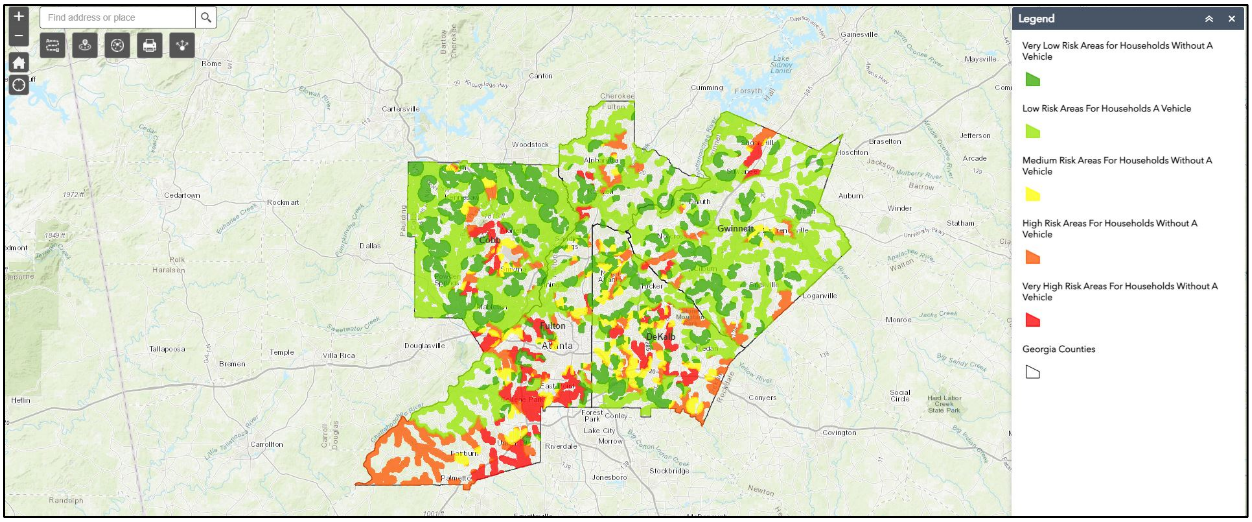

Figure 9. Vulnerability of Households With No Vehicle with the Red, Orange, Yellow, Light and Dark Green Colors Showing Diminishing Levels of Social Vulnerability

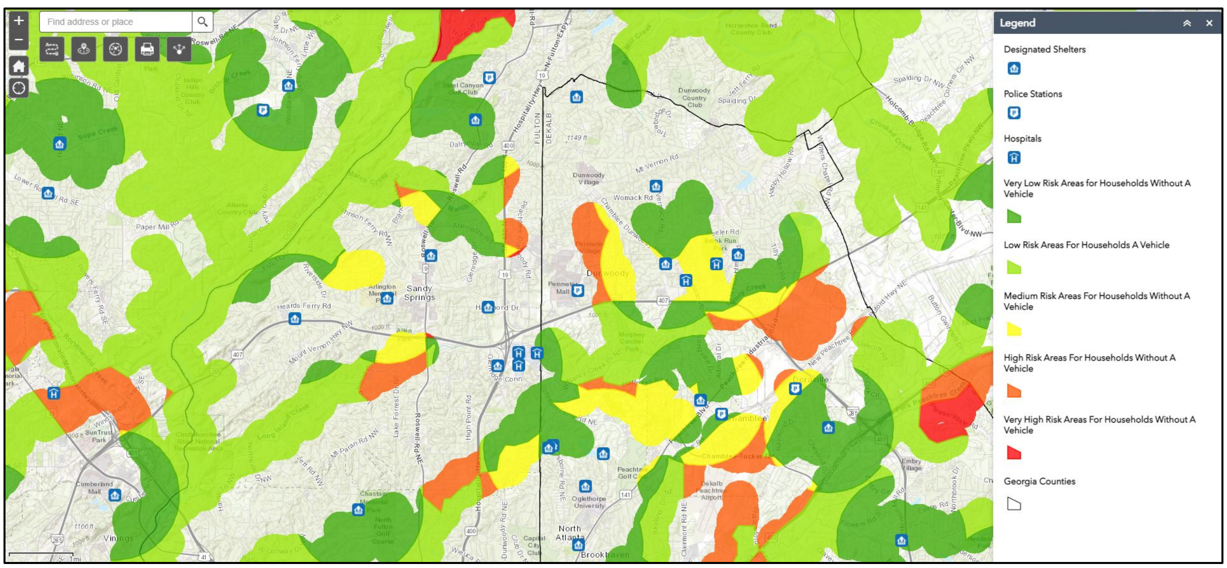

Figure 10. Location of Author to Nearby Shelters with the Shelters Shown in Blue and the Red, Orange, Yellow, Light and Dark Green Colors Showing Diminishing Levels of Social Vulnerability

Chapter 4 The Web Mapping Application

The importance of providing shelter during floods is essential for planning to evacuate or shelter in place. As seen in the previous section, not everyone can evacuate due to not having a vehicle, disability, age, and many other factors. This is why the AMWA may improve the public's understanding of flood vulnerabilities and how to prepare for a flood event. This chapter explains the features of the AMWA and how it is made user friendly so everyone can view and use it for the intended purposes.

4.1. Creating the Web Mapping Application

ArcGIS Online (AGOL) was used to create the web application after publishing the feature hosted layers in ArcMap and importing them into AGOL. They were edited in the map viewer by changing the pixel size and symbols to accommodate the volume of shelters, police stations, and hospitals. The visibility range was used to allow these features to appear and disappear when the user zoomed in and out. The visibility range was added for each layer to create different views of the map.

The Web AppBuilder in AGOL can generate a web mapping application from any web map a user has in their content. The foldable theme was selected to create the web application with social vulnerability calculated from all of the layers that were previously imported and edited.

The foldable theme is a simple web mapping application that provides five slots for different widgets selected by the app creator. The widgets are the critical component of the web mapping application because of the functionality they provide. The first widget was the direction widget because it allows the user to choose a beginning and end location by either exposing their location or providing the address. When providing this information, a user can select driving time and distance or walking time and distance, to assist individuals who may need to evacuate to the nearest shelter.

The second widget is the near me tool. This allows users to locate the nearest shelter, police station, and hospital within a 1-mile radius. This widget enables the user to enter an address and then shows the shelters that are closet to them, and by including the flood hazard, users can also determine if any of these shelters are in the flood plain and allow them to choose another shelter if a shelter, hospital, or police station near them. The near me tool delineates the shortest paths in the app to the shelters, police stations, and hospitals.

The third widget is the analysis widget, which can help a user construct a social vulnerability map based on the variables they select by using the additional information provided in the social vulnerability attribute table.

The final print widget was provided so users could print out instructions for travel to the nearest shelter in the case of a power failure or if a mobile device dies.

4.2. Webpage Design

The final design of the web application can be accessed at https://gis-web.usc.edu/devintho/dthomas/AtlantaFloodPreparation.html. All the coding was completed in Sublime Text 3 using Windows. Using the w3schools as a guide, HTML and CSS were used to adjust the interface, navigation taps, typography, and instructional video. Links were also incorporated to give users the necessary tools to better prepare for a flood event and receive updates when clicking on the link.

The web mapping application is the focus of the webpage due to it being visual and interactive. However, on the webpage, there are links provided in the navigation bar that allows users to be directed to other websites. These websites provide the important information, including weather updates, how to prepare a disaster kit, and emergency updates.

The overall design of the webpage illustrates the importance of preparing users for an upcoming flood event. The design of the app is simple to facilitate a variety of different users efficiently working through the application to acquire understanding of the information provided (Figure 11).

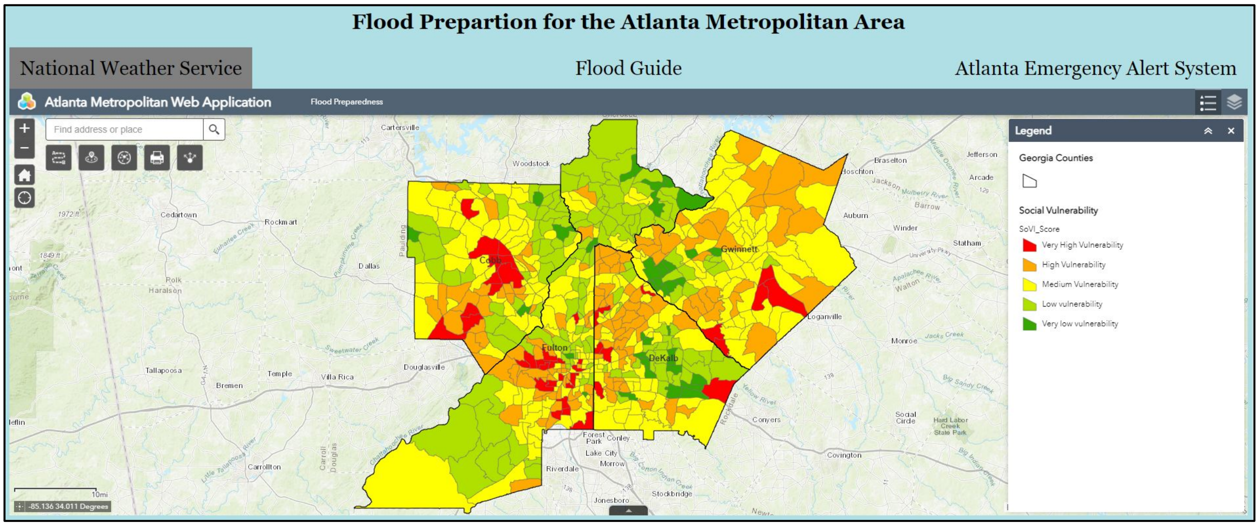

Figure 4. Screenshot showing the initial page in the AMWA. The colors in this map refer to different levels of social vulberability based on the PCA Analysis

Chapter 5 Conclusions and Recommendations

The web mapping application aims to help residents better prepare for a flood event. This chapter describes the issues experienced during the thesis, things that went well, and future work that would improve the heft and overall usability of the AMWA.

5.1. Issues

The first significant issue occurred when developing a social vulnerability map. The original social vulnerability studies did not use PCA for the variables but instead calculated vulnerability based on the averages and standard deviations to build social vulnerability maps (Cutter et al. 2000). The initial idea entailed using the social vulnerability map for background information. The FEMA data can be used to calculate physical vulnerability for each census tract in AGOL using the method explained in Chapter 3. This required new data to be collected and knowledge of PCA, which was difficult given the fact the author has not encountered this approach before.

The other issue is the webpage design became corrupted, and the webpage had to be recreated, which was a challenge because the webpage was created in the summer of 2020 and it took some time to create the HTML and CSS that was needed to recreate the original application.

5.2. Future Work

The AMWA developed in this thesis project could be extended and enhanced. Further work, for example, could include the development of a full-scale web mapping application for Georgia that provides real-time updates. The four selected counties were the most affected by the 2009 flood, but Georgia continues to experience flood events in a variety of locations though not as catastrophic as the 2009 floods experienced in and near Atlanta. Incorporating live streams documenting closed roads and providing a messaging system or tool in the web app to indicate shelter occupancy rates would help users to evacuate more efficiently and know which shelter to go to next (see Shahabi and Wilson (2014, 2017) for examples).

Better estimates of physical vulnerability based on elevation and landscape position would have helped as well (e.g. Zachos et al. 2016). Developing a physical vulnerability map for the web application would be the next step by including critical facilities, buildings, and transportation networks. Also including flood depth would further display the potential areas to be affected and would give users a better representation. This could be accomplished by using Digital Elevation Models, LiDAR, and Flood Insurance Rate Maps to access the impact of flooding on transportation networks and infrastructure.

The final and most important innovation of all would be the development of a mobile application for iOS and Android. Adding these capabilities would allow users to access the application from anywhere and give the user a better opportunity to evacuate and continually check the application for updates, irrespective of whether they were at home, work, or in motion.

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Appendix A Webpage Code

```
<html lang="en"> <head>
<title>Atlanta Flood Preparation</title>
<style>

body {background-color: powderblue; text-align: center; font: 100% Georgia, "Times New Roman",Times, sans-serif;}

p  {color: black; text-align: center; font:Georgia, "Times New Roman",Times, sans-serif;}
.esri-home.esri-widget--button.esri-widget {
width: 42px;
height: 42px;}
.esri-icon.esri-icon-home {font-size: 24px;}
.topnav {overflow: hidden;}
.topnav a {float: left; color: black;text-align: center;padding: 14px 16px;text-decoration: none;font-size: 30px;}
.topnav a:hover {background-color: gray;color: black;}
.topnav-centered a {float: none;position: absolute;top: 50%;left: 50%;
transform: translate(-50%, -641%);}
.topnav-right{float:right;}

</style>
</head>
<body>
<header>
		<h1>Flood Prepartion for the Atlanta Metropolitan Area </h1>
</header>
<div class="topnav">
<a href="https://water.weather.gov/ahps">National Weather Service</a>
<div class="topnav-centered">
<a href="https://www.ready.gov/floods">Flood Guide</a> </div>
<div class="topnav-right">
<a href="https://www.atlantawatershed.org/prepare-for-emergencies">Atlanta Emergency Alert System</a></div></div>
<iframe width="100%" height="650px"
src="https://uscssi.maps.arcgis.com/apps/webappviewer/index.html?id=dccdf9a432cd4512877870773e365b2f" frameborder="0"
scrolling="yes"></iframe>
<br>
<h2> APPLICATION DESIGN </h2>
<p>The following web application is intended to provide users with the necessary information to prepare for a flooding event.
The information provided is a combination of information from different agenices and therefore the map is as current as the data
from the agencies. </p>
<br>
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<br>
<br>
<p>
<span>Devin Thomas  |  University of Southern California  |  2020
</span></p>
</body>
</html>
```